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Distribution Changes of Chinese Skink (*Eumeces chinensis*) in China: the Impacts of Global Climate Change

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Abstract Repaid global climate changes in temperature and rainfall influence the species distribution and diversity patterns. Chinse skink is a common species with large population and widely distribution in China. To access potential effect of climate changes on the unendangered species, we used the maximum-entropy modeling (MaxEnt) method to estimate the current and future potential distributions of Chinese Skink. Predictions were based on two periods (2050 and 2070), three general circulation models (GCMs: BCC-CSM1-1, HadGEM2-ES, MIROC5), four representative concentration pathways (RCP: 2.6, 4.5, 6.0 and 8.0) and 28 environmental variables including topography, human impact, bio-climate and habitat. We found that the model were better fit with high values in AUC, KAPPA and TSS. The jackknife tests showed that variables of BIO9, BIO14, BIO15, HFI and GDP were relatively higher contributions to the model. Although the size of suitable areas for skink have less effect by future climate change under full and mull dispersal hypothesis, we should still focuse on the effect of human impact and climate changes on the protection and management for Chinese skink due to the variables uncertainty.

Keywords climate change, MaxEnt, prediction, species distribution model, unendangered species

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1. Introduction

Many evidences indicated that rapid global climate change is already undergoing. Global average temperature has increased by 0.85°C from 1880 to 2012, and this trend is likely to continue for decades (Stocker *et al.*, 2013). According to the most recent Intergovernmental Panel on Climate Change Fifth Assessment Report (IPCC AR5), the global average temperature may increase further by a minimum of 0.3–1.7°C (RCP 2.6) to a maximum of 2.6–4.8 °C (RCP 8.5) by the end of this century. Continuing global warming forced the species to response the climate change by expansion or contraction their native range, thus affected the global diversity by some biological events, such as habitat destruction, fragmentation and biological invasion (Pearson *et al.*, 2007; Lyu and Sun, 2014; Penman *et al.*, 2010).

To investigate the changes of species distributions and diversity patterns under climate change, many species distribution models (SDMs) were developed and applied to detect the relationships between species distribution and environmental variables(Elith *et al.*, 2006; Peterson, 2006). Although recent studies pointed out some drawbacks of SDMs, including neglecting competitive interactions, species plasticity, adaptation and time-lag (Davis *et al.*, 1998; Hannah *et al.*, 2002; Pearson and Dawson, 2003), SDMs could still be regarded as the useful models for predicting species potential distribution and extinction risk, assessing reserve designs, and evaluating conservation priorities by incorporating meta-population demography and landscape interactions, species life history traits, biotic interactions, species dispersal ability, species evolution and adaptation, and human activities and disturbances into the models (Keith *et al.*, 2008; Preston *et al.*, 2008; Li *et al.*, 2014; Luo *et al.*, 2014).

Comparing to the mammals and birds, the poor dispersal

ability and autonomic thermoregulation lead to the reptiles are more sensitive to the climate change. Previous studies on reptiles were focused on the potential distribution prediction on some endangered and invasive species. However, the species with a stable population and wide distribution is less studied to our knowledge. Chinese skink (*Eumeces*[=*Plestiodon*] *chinensis*) is medium-large sized oviparous scincid lizard, widely distributing in East Asia including China, Korea and Vietnam (Lin *et al*., 2006). Based on the previous ecology studies, the main habitat for Chinese skink is lowland area including farmland, forest, and roadside (the altitude ranging from 10 to 1030 m), so the population size of this species is stable because of the strong environment adaptiveness (Pan *et al*., 2005).

In this study, we selected the Chinese Skink as the model species using MAXENT model to simulate the potential distribution under different climate change scenarios for 2050 and 2070. The aims of this study are: 1) to determine the current and future potential distribution of *E. chinensis*; 2) to find out the most important environmental factors in model predicting; 3) to compare the future distribution pattern of *E. chinensis* to the species with small population size and narrow distribution under future climate scenarios; 4) thus to provide recommendations for the protection and management of *E. Chinensis* in China.

2. Methods and Materials

2.1. Occurrence Data and Environmental Variables We collected species occurrence data from 3 sources: 1) network databases, including Global Biodiversity Information Facility (GBIF: http://www.gbif.org/), Specimen Resources Sharing Platform for Education (SRSPE: http://mnh.scu.edu.cn/main.aspx) and China Animal Scientific Database (CASD: http://www.zoology.csdb.cn/page/index.vpage); 2) the records in the herpetological museum of Chengdu institute of biology (CIB), Chinese academy sciences (CAS); 3) the information on the published literatures (all the data accessed in December 2014). To ensure that only one record in each grid cell, we removed duplicate records in the same 1 km^2 grid cell. Totally 79 grid localities were kept for the following procedures.

We collected 28 environmental variables and divided them into 4 categories: topography, human impact, bio-climate and habitat. The codes, source and resolution of each variable were shown in Table S1. The correlation between the candidate environmental variables was analyzed by the band collection statistics function in ArcGIS 10.2. We removed highly correlated variable (r > 0.7) to minimize the impact of multicollinearity and over-fitting of the model (Burnham and Anderson, 2002). Finally, BIO3, BIO 5, BIO9, BIO14, BIO15, ELE, SLP, ASP, LAC, NDVI, POP,GDP, HFI were kept in the next model construction.

2.2. Global Change Scenarios For projecting future climate scenarios, we selected three internationally recognized general circulation models (GCMs): BCC-CSM1-1, HadGEM2-ES, MIROC5 based on the Coupled Model Intercomparison Project Phase 5 (CMIP5: http://cmip-pcmdi.llnl.gov/cmip5). According to IPCC AR5 on greenhouse gas scenarios, we selected representative concentration pathways (RCP: 2.6, 4.5, 6.0 and 8.0) in two time periods (2050 and 2070) (Moss *et al*., 2008). To reduce the uncertainty and illustrate future climate conditions, we averaged three GCMs for each RCP scenario to produce a total of 8 future models (four for the 2050s and four for the 2070s). Because we could not projected future scenarios to the factors of habitat (AI, LAC and NDVI), human impact (POP, GDP and HFI) and topography (ELEV, SLP, and ASP) (Table S1), we assumed these factors were constant, and used them in these future predictions (Luo *et al*., 2014; Thuiller *et al*., 2006).

2.3. SDM construction and evaluation We used MAXENT 3.3.3 to prediction the Chinese skink distribution. The settings for the this software were as following: 1) regularization multiplier, 1; 2) maximum iterations, 500; 3) convergence threshold, 10^{-5}; 4) maximum number of background points, 10 000; 5) random test percentage, 20%; 6) replicates, five; We selected the 'auto features' dependent on the number of presence records to reduce over-fitting (Phillips *et al*., 2006). We selected a logistic output format to keep the environmental suitability values ranging from 0 to 1, and carried out jackknife analyses of the regularized gain with training data to examine the importance of individual predictors.

To evaluate the accuracy of each model, we firstly selected the AUC the area under the receiver operating characteristic (ROC) curve. AUC values ranged from 0 to 1, and models with values above 0.75 are considered potentially useful (Fielding and Bell, 1997). To test the reliability of the accuracy assessment, we then calculated Cohen's kappa and true skills (TSS), which are both ranged from–1 to 1. Values 1 indicated a perfect performance, while values 0 indicated a performance no different to random (Burnham and Anderson, 2002). We used the *presence.absence.accuracy* function of the *R* package *PresenceAbsence* to calculate the kappa and TSS values (Freeman and Moisen, 2008).

2.4. Impacts of Climate Change We first selected the thresholds by the method of minimum training presence and transferred raw outputs to presence absence maps (Pearson *et al*., 2007). Then two spread assumptions were used to calculate the range shift under climate change: 1) null spread (no spreadability of Skink); 2) full spread (unlimited ability to spread). Under the assumption of null spread, only the overlap habitat between current and future ranges was considered suitable for Skink. Under the full spread assumption, the Skink

populations could reach all new potential habitat ranges. We finally quantified the predicted current range (*CR*), potential range loss (*RL*, current suitable areas projected to be lost), and potential range gain (*RG*, current unsuitable areas projected to become suitable) by summing them by pixel, and calculated the *RL* and *RG* rates by dividing each by *CR*. Furthermore, we estimated the percentages of range change (*RC*) and range turnover (*RT*) using the following equations (Hu and Jiang, 2011):

$$RC = 100\times (RG-RL)/CR$$

$$RT = 100\times (RG + RL)/(CR + RG)$$

3. Results

3.1. Model Performance and Variable Importance Values of kappa and TSS were both larger than 0.7, and the AUC values were larger than 0.9, which indicated that the SDMs were better fit for the Chinese Skink. And the five replicates for cross-validation were stable indicated that the model was robust (Table 1). The jackknife test showed that the training gain with all variables is 2.57 (n = 5), and them for each variable ranged from 0.0264 to 1.6125. Variables of BIO9, BIO14, BIO15, HFI and GDP achieved the highest gains when used in isolation indicated that they had relatively higher contributions to the model (training gain with only the variable > 1.10). However, other variables including ELEV, ASP, SLP, BIO3, BIO5, LAC and NDVI had limited contributions to the model (training gain with only the variable < 1.10) (Figure 1). Variable contributions analysis showed that BIO14 had the highest contribution (52.0%) to the model followed by HFI with a 27.7 % contribution, but POP and BIO15 had the lowest contribution (0.2%).

3.2. Current and Future Potential Distributions and Range Shifts under Climate Change Based on the current suitability map, Chinese Skink is predicted with high habitat suitability in the southeast China with redder color, where is in the lower altitude region with more rainfall and higher mean temperature (Figure 2). According the threshold method of 10 percentile training presence, the average values of the cutoff point is 0.156 (n = 5). With the threshold at 0.156, the potential suitable area size for Chinese Skink is 1605446 km^2 at present, only accounts for 11.6% of the study area.

To estimate the climate change impact, the potential distributions of Chinese Skink in 4 future climate scenarios were shown in Figure 3. Under the full dispersal hypothesis, the potential distribution in all four RCP scenarios is expected to increase by the 2050s (average range size = 1721108 km^2, n = 4)

Figure 1 Results of jackknife test of relative importance of predictor variables for Chinese Skink.

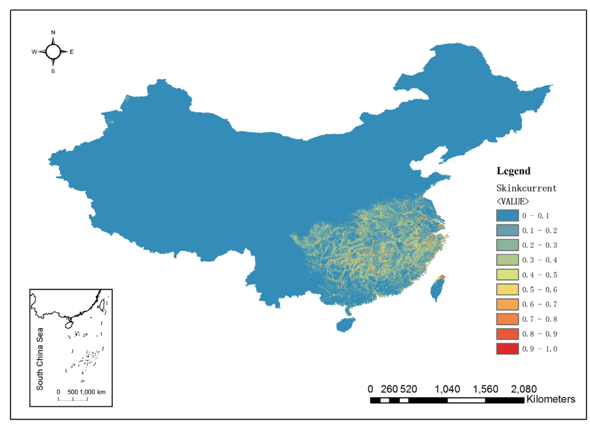

Figure 2 Mean predicted probability of occurrence (suitability) of Chinese Skink under current situation in China. The color represents the suitability, from low (blue) to high (red).

Table 1 Accuracy measurements of predictive SDMs for Chinese Skink. AUC: area under relative operating characteristic curves; TSS: true skill statistic; Kappa: Cohen's kappa statistic; Rep.1–5 represent the five replicates for cross-validation.

Accuracy measurement	Ensemble	Rep.1		Rep.2		Rep.3		Rep.4		Rep.5	
		Training	Test	Training	Test	Training	Test	Training	Test	Training	Test
kappa	0.774	0.800	0.783	0.794	0.724	0.798	0.631	0.803	0.756	0.803	0.847
AUC	0.982	0.979	0.980	0.979	0.985	0.980	0.985	0.978	0.985	0.980	0.985
TSS	0.748	0.766	0.783	0.799	0.703	0.741	0.523	0.803	0.713	0.803	0.847

Table 2 Areas of potential distributions and percentages of range loss (*RL*), range gain (*RG*), range change (*RC*) and range turnover (*RT*) of Chines Skink for Current, 2050, and 2070 under the climate change, based on the full dispersal and null dispersal hypothesis.

		Area (km^2)	*RL* (km^2)	*RG* (km^2)	*RC* (%)	*RT* (%)
current		1605446				
Full dispersal hypothesis						
2050	rcp2.6	1692317	44541	131412	5.41%	10.13%
	rcp4.5	1767885	50514	212953	10.12%	14.49%
	rcp6.0	1682396	29164	106114	4.79%	7.90%
	rcp8.5	1741832	61520	197906	8.50%	14.39%
2070	rcp2.6	1684729	46666	125949	4.94%	9.97%
	rcp4.5	1726442	50463	171459	7.54%	12.49%
	rcp6.0	1637441	74099	106094	1.99%	10.53%
	rcp8.5	1841842	51490	287886	14.72%	17.92%
Null dispersal hypothesis						
2050	rcp2.6	1560905	44541	0	−2.77%	2.77%
	rcp4.5	1554932	50514	0	−3.15%	3.15%
	rcp6.0	1576282	29164	0	−1.82%	1.82%
	rcp8.5	1543926	61520	0	−3.83%	3.83%
2070	rcp2.6	1558780	46666	0	−2.91%	2.91%
	rcp4.5	1554983	50463	0	−3.14%	3.14%
	rcp6.0	1531347	74099	0	−4.62%	4.62%
	rcp8.5	1553956	51490	0	−3.21%	3.21%

and further increase by the 2070s (average range size = 1722614 km^2, n = 4), respectively. However, the potential distribution under the null dispersal hypothesis showed an opposite tendency, all the potential distribution in 4 future RCP scenarios will decrease by the 2050s (average range size = 1559011 km^2, n = 4) and by the 2070s (average range size = 15497766 km^2, n = 4) (Figure 3, Table 2).

Across all scenarios in 2050s and 2070s, range loss (*RL*) under the full dispersal hypothesis were larger than that under the null hypothesis (Independent T test, t =7. 353, df = 14, P < 0.01). Also from the values of range gain is 0 under the null dispersal hypothesis, because we assumed that the Skink could not expand their distribution by migration. Range gain (RG) is ranging from 106114 to 287886 km^2, growing from 6.61%–17.93% to the current area, it indicated that the Skink will expand its suitable range under no limit on its dispersal. Range change is ranging from 1.99% to 14.72% under the full dispersal hypothesis, but ranging from −1.82% to −4.62% under the null dispersal hypothesis, which indicated that the predicted potential suitable habitat for Skink present different results based on the species' migrate ability.

4. Discussion

4.1. Sensitivity to Climate Change Many researches indicated that the global climate is undergoing rapid change, and is predicted to continue over the next century. The climate change on the earth is predicted to warm by 0.6 ± 0.2 °C during the 20th century and by 1.4–5.8 °C in 21th century (Houghton *et al.*, 2001). Warming of the earth may pose a threat to species by affecting population dynamics, distributions and the spatial structure of the suitable habitats (Bellard *et al.*, 2012). Some studies predicted that changing climate will reduce the suitable habitat and narrow the distribution range, which will drive 11% to 58% of vertebrate, invertebrate, and plant species to extinction by 2050 (Thomas *et al.*, 2004). While some species are likely to benefit from the changes with extending ranges into currently unoccupied areas (Parmesan *et al.*, 1999; Morueta-Holme *et al.*, 2010).

Most animal species may have at least limited dispersal ability and may not be able to colonize all of their climatically suitable area if other habitat requirements are not fulfilled (Levinsky *et al.*, 2007). Full- and Null-constraint migration assumptions are the two extreme possibilities, and future range shifts will probably fall in between (Levinsky *et al.*, 2007; Hu and Jiang, 2010; Luo *et al.*, 2014). Chinese skink is a medium-large sized oviparous scincid lizard with ~134 mm snout-vent length (SVL), the population of this species is stable and wide distribution (Lin *et al.*, 2006). Assume on the full spread hypothesis, our results predicted that the range loss (*RL*) of

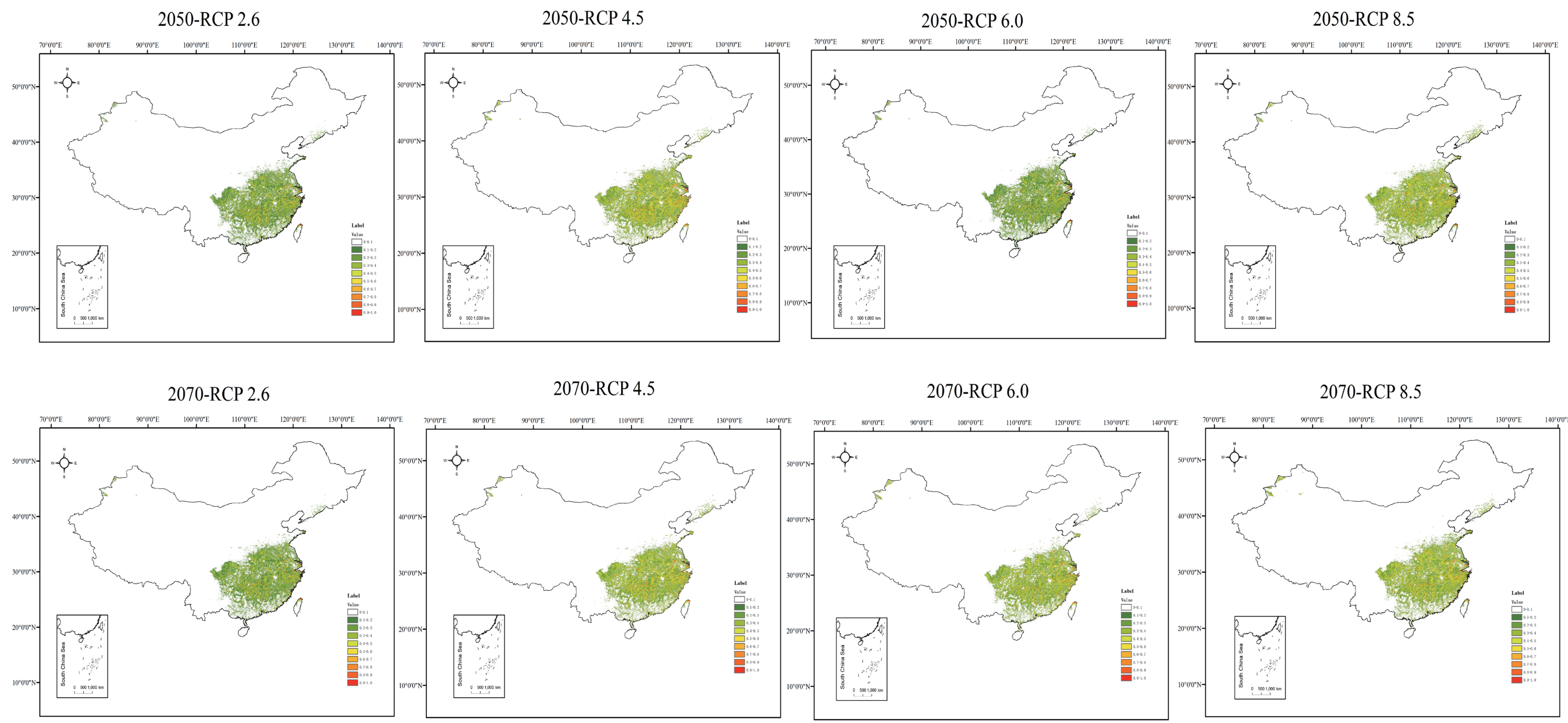

Figure 3 Predicted the future habitat suitability for Chines Skink in 2050 and 2070 under climate change. These predictions were obtained with an ensemble-forecast approach across three general circulation models (BCC-CSM1-1, HadGEM2-ES, MIROC5) and four emission scenarios (rcp2.6, rcp4.5, rcp6.0 and rcp8.5) from IPCC AR5.

Chinese skink is 2.89% (1.82% to 3.83%) by 2050s and 3.47% (2.91% to 4.62%) by 2070s, but range gain (*RG*) is 10.1% (6.60% to 13.26%) by 2050s and 10.77% (6.61% to 17.93%) by 2070s. We found that the range gain is much larger than the range loss for Chinese skink resulting from several climate change scenarios, which indicated that the current habitat of high occurrence probability is still be useful, and some current unavailable habitat could also be used in future. Even under the null dispersal hypothesis, Chinese skink were assumed that no migrate ability (*RG* = 0), the proportions of *RL* is relative small (2.89% by 2050s and 3.47% by 2070s). Most of the current suitable habitat is still with high occurrence probability by Chinese skink in future climate scenarios (*RT* < 15% in both hypotheses) (Table 2). Thus, depending on the population size, moment ability, suitable habitat, our modelling revealed that the suitable habitat of Chinese Skink was less affected by future climate change.

4.2. The Importance of Environmental Variable Influencing the Future Distribution Previous researches in species distribution models to predict the potential distribution were focused on the bio-climate, topography and habitat factors (Pearson *et al*., 2007; Keith *et al*., 2008; Penman *et al*., 2010). Recently studies are paid more attention to the anthropogenic activity, because human activities represent the extensive, long-duration and persistent impacts on the environment that permanently alter ecosystem construction and ecology (Hu and Jiang, 2011; Li *et al*., 2014; Luo *et al*., 2014). As a result, we added the human impact into the MAXENT model. The Jackknife analysis in this study showed that the candidate factors in both bio-climate (BIO9, BIO14, BIO15) and human impact (HFI and GDP) groups influencing the distribution and patterns of range change (training gains > 1.0), however, factors in topography and habitat have limited effect on model prediction (training gain < 1.0) (Figure 1). Precipitation (BIO14 and BIO15) and temperature (BIO9) represented the future climate changes in hydrothermal condition are benefit for Chinese Skink in prey and incubation (Ji and Zhang, 2000; Ji *et al*., 1995).

Human impact (HFI and GDP) are other key factors contributed to the modelling prediction with training gains > 1.0 (Figure 1). Previous ecology studies indicated that Chinese skink preferred the ecosystem changed by humans, such as farmland, grass and brushwood on the roadside (Lin *et al*., 2006). And diets of Chinese Skink are mainly consisted to the invertebrates (annelid, molluscan and arthropod) covering more than 30 families (Lin and Ji, 1999). Human activity such as farming, harvest-picking and lumbering changed the habitat from coverage to open, which means that Chinese Skink could increase the detective probability on prey. Therefore, the increasing temperature, rainfall and human impact will not only keep most of the existing suitable habitat for Chinese Skink, but also enlarge its range into some current unoccupancied region. Although this study does not necessarily provide accurate predictions of current and future distributions due to the small sample size and environmental data accuracy, it is a first model prediction on Chinese Skink under climate change and human activities in China and the results are still convinced that could be used to design the conservation plan for this species.

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Appendix

Table S1 Environmental Variables Used for Modeling of Chinese Skink (All the Variables were Compiled in WGS 1984).

Variable groups	Environmental variables	Codes	Data sources	Resolution
Bioclimate	Annual Mean Temperature	Bio1	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Mean Diurnal Range (Mean of monthly (max temp - min temp))	Bio2	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Isothermality (BIO2/BIO7) (* 100)	Bio3	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Temperature Seasonality (standard deviation *100)	Bio4	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Max Temperature of Warmest Month	Bio5	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Min Temperature of Coldest Month	Bio6	Worldclim 1.4,http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Temperature Annual Range (BIO5-BIO6)	Bio7	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Mean Temperature of Wettest Quarter	Bio8	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Mean Temperature of Driest Quarter	Bio9	Worldclim 1.4,http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Mean Temperature of Warmest Quarter	Bio10	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Mean Temperature of Coldest Quarter	Bio11	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Annual Precipitation	Bio12	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation of Wettest Month	Bio13	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation of Driest Month	Bio14	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation Seasonality (Coefficient of Variation)	Bio15	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation of Wettest Quarter	Bio16	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation of Driest Quarter	Bio17	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation of Warmest Quarter	Bio18	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
	Precipitation of Coldest Quarter	Bio19	Worldclim 1.4, http://www.worldclim.org/cmip5_30s	~1 km^2 (30-seconds)
Topography	Elevation (m)	ELEV	Global digital elevation model, http://srtm.csi.cgiar.org/	~1 km^2 (30-seconds)
	Slope (°)	SLP	Calculated based on ELEV by the slope function in ArcGIS 10.2	~1 km^2 (30-seconds)
	Aspect (°)	ASP	Calculated based on ELEV by the aspect function in ArcGIS 10.2	~1 km^2 (30-seconds)
Habitat	Aridity index	AI	CGIAR-CSI Global-Aridity and Global-PET Database, http://www.cgiar-csi.org/data/global-aridity-and-pet-database	~1 km^2 (30-seconds)
	Habitat Landcover type	LAC	Global Landcover 2000, http://ies.jrc.ec.europa.eu/global-land-cover-2000	~1 km^2 (30-seconds)
	Normalized difference vegetation index	NDVI	Thematic Database of Human-Earth System, http://www.data.ac.cn/	~1 km^2 (30-seconds)
Human impact	Human population (individuals/km^2)	POP	Thematic Database of Human-Earth System, http://www.data.ac.cn/	~1 km^2 (30-seconds)
	Gross domestic product (104 Chinese Yuan/km^2)	GDP	Thematic Database of Human-Earth System, http://www.data.ac.cn/	~1 km^2 (30-seconds)
	Human footprint index	HFI	Last of the Wild Data, http://sedac.ciesin.columbia.edu/wildareas/	~1 km^2 (30-seconds)